Community Coalitions as a System: Effects of Network Change on Adoption of Evidence-Based Substance Abuse Prevention

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Objectives. We examined the effect of community coalition network structure on the effectiveness of an intervention designed to accelerate the adoption of evidence-based substance abuse prevention programs.

Methods. At baseline, 24 cities were matched and randomly assigned to 3 conditions (control, satellite TV training, and training plus technical assistance). We surveyed 415 community leaders at baseline and 406 at 18-month follow-up about their attitudes and practices toward substance abuse prevention programs. Network structure was measured by asking leaders whom in their coalition they turned to for advice about prevention programs. The outcome was a scale with 4 subscales: coalition function, planning, achievement of benchmarks, and progress in prevention activities. We used multiple linear regression and path analysis to test hypotheses.

Results. Intervention had a significant effect on decreasing the density of coalition networks. The change in density subsequently increased adoption of evidence-based practices.

Conclusions. Optimal community network structures for the adoption of public health programs are unknown, but it should not be assumed that increasing network density or centralization are appropriate goals. Lower-density networks may be more efficient for organizing evidence-based prevention programs in communities. (*Am J Public Health.* 2007;97:880–886. doi:10.2105/AJPH.2005.063644)

Community coalitions are often formed to help communities mobilize resources and coordinate activities that improve the public's health.[1–3] Conceivably, coalitions may contribute to all phases of health program delivery, from planning to implementation and sustainability.[4,5] Most important, however, may be the role of coalitions in assisting communities with identifying, planning, and subsequently adopting effective health programs. In this regard, community coalitions may be best served by the promotion of evidence-based programs—those that have been systematically evaluated and shown to be effective in changing health-related behavior. One area in which evidence-based standards and programs have been well articulated is drug abuse prevention.[6,7] Coalitions are particularly important to the delivery of drug abuse prevention programs because coalitions include constituents and prevention stakeholders from many perspectives.[8] By bringing together representatives from local government, law enforcement, education, media, parent groups, health agencies, and businesses, coalitions can provide a community forum for identifying, planning, and adopting prevention programs that would not otherwise be possible through the efforts of a single agency.

Several features of coalitions affect their performance.[9] One factor is having a clearly articulated structure in which subcommittees make decisions and assign tasks.[10,11] Other factors include professional representation (whether representatives from various professions are in the coalition), the variety of key stakeholder roles represented, participation (i.e., the frequency with which members attend meetings), and membership tenure.[12,13] Notably missing in the study of coalition effectiveness is attention to the coalition's communication network, i.e., who is connected to whom and how those connections affect outcomes.[14–16] Social network analysis has shown how social network properties affect the adoption of health-related behaviors, such as smoking[17,18] and contraceptive use.[19,20] Network analysis also is used to study interorganizational relations, because these relations are believed to affect the delivery of health services[3,14] and are useful for creating community capacity.[3,16] By adopting a network perspective in the study of coalitions, we hope to expand the potential of social network analysis for measuring social capital.[21–23]

The field of network theory and analysis is well established, but it has had little application to prevention.[24–26] Of the many different network indices, 2 may have the most potential for representing a coalition's structure: density and centralization. For example, studies of the diffusion of innovations have shown that network density and network centralization are positively associated with faster diffusion of innovations.[26] Dense networks provide more pathways where communication about prevention programs can flow compared with sparse networks. Conversely, sparse networks may not provide enough pathways for information to be circulated throughout the coalition. Density also may facilitate diffusion, because dense networks may reflect a cohesive normative environment.[3] A network with many links is more likely to have members who share common values or beliefs. Thus, a dense network may reflect a homogenous coalition, and this homogeneity will facilitate information exchange and decisionmaking.[20]

Additionally, centralized networks—those with ties directed at 1 or a few members—are expected to facilitate the adoption of evidence-based programs. Centralized networks have hubs that can disseminate information to many other members quickly. A centralized coalition has leaders who can enact decisions more readily, because they have positions of power and control.[27] Moreover, once central members in a centralized network adopt a program, they are able to locate the right coalition members to implement that program. On the basis of these findings, we expect the adoption of evidence-based practices to be greater among dense coalitions than among sparse ones, and adoption should be greater among centralized networks than among decentralized ones. However, other structural characteristics, such as whether a coalition operates as a single group or as multiple subcommittees, may mitigate these relationships.[11]

In a highly structured coalition, denser networks (those with a high volume of connections) may not facilitate efficiency or progress.[28] First, lower density within a network may reflect more formal collaborations.[29] Second, although there is probably a minimum density level within a network needed for coalitions to adopt innovations, once this level is reached—particularly in structured coalitions—too much density may be a liability. Too much density within a network can create communities with too few connections to external information and resources, thus making them disadvantaged.[26,30,31] Finally, organizational studies have shown that too much density within a network can hurt performance.[32,33]

Similarly, networks that are too centralized concentrate power, which may result in less shared decisionmaking and lower commitment to prevention programs among noncentral members. Centralized networks are referred to as hierarchical networks, and studies have shown that employees in hierarchical organizations feel less satisfied with their work.[34–36] Some researchers have advocated for decentralized or horizontal communication networks as being more appropriate for organizations that use electronic communication technology.[37] Therefore, although a centralized network is more efficient,[38] a decentralized one may be more empowering. Thus, the adoption of new programs may be facilitated in sparser or more decentralized networks.

Steps Toward Effective Prevention (STEP) was a large prevention diffusion trial that included a community coalition intervention component.[4,6] We evaluated the effects of this intervention on changing the coalition's network density and centralization. We also evaluated the mediating effects of network change (change in network density or centralization) on subsequent planning and adoption of evidence-based prevention programs. The intervention was designed to increase the efficiency of coalition networks in planning and implementing evidence-based prevention programs by creating an organized coalition where one had previously not existed and by creating more decentralized task work groups where there had been only a single group. At least 2 previous studies have shown that the achievement of benchmarks is significantly associated with the adoption of prevention plans.[11,39] We used network analysis methods to measure the coalition structures and explore how the dynamics of the coalition system affected the coalition's ability to implement drug abuse prevention programs. On the basis of previous research, we hypothesized that the intervention would increase the efficiency of existing coalitions by decreasing the networks' density and centralization, which in turn would positively affect the progress and adoption of prevention planning.

METHODS

Our study was part of a larger trial—STEP—that evaluated the dissemination of evidence-based drug prevention programs to 24 cities. Small- to medium-size cities (populations = 20 000–104 000) were recruited from Massachusetts, Colorado, Arkansas, Iowa, and Missouri to participate in a 5-year randomized trial. The selected cities were considered underserved with regard to drug prevention (i.e., few funds for prevention, no state incentive grants, and no evidence-based programs). STEP used relatively low-cost interactive up-and-down-link satellite television training to deliver 6 evidence-based prevention programs over a 3-year period. At baseline, 67% of the cities had an existing coalition that ranged in longevity from 2 to 25 years, 21% had created a prevention coalition specifically for STEP, and 12% had only an occasional grouping of community leaders.

Research and Measurement Designs

Cities were matched with 2000 US Census data on demographic variables associated with risk for drug use (percentage of the population that was male, younger than 18 years, White, or had income below the federal poverty level). Matched cities were then assigned within each state to 1 of 3 conditions: televised prevention training plus technical assistance, televised prevention training only, or prevention as usual (control). The data in our study are from baseline (fall 2001) through 18-month follow-up (spring 2003).

Study Participants

Community leaders were identified and recruited through a process of snowball sampling,[11] which included 3 criteria: (1) representing 1 or more prevention stakeholders (education, law enforcement, parent groups, youth services, media, local government, business, health or medical profession, special or minority interest group), (2) being—or having the potential to be—a positive role model for youth, and (3) willing to participate in a prevention coalition for 2 years. This sampling process resulted in a list of 1041 potential participants (39–179 per city). Among these respondents, 1 community leader in each city was identified and trained annually to serve as a site facilitator for STEP, which included organizing other leaders for training and meetings, facilitating data collection, and collecting archival data on meeting process. From the list of potential participants, site facilitators identified 709 individuals from the 24 cities who were considered to be active in terms of having attended at least 1 community or coalition meeting during the previous 12 months.

Respondents completed both a community leader survey and a network survey. Of the 709 active leaders, 670 (94.5%) completed either the community leader or network survey at baseline, and 415 (58.5%) completed both; at 18-month follow-up, data were collected from 406 (57.3%) leaders, and 255 leaders (36% of 709 active leaders at baseline) had completed surveys at both waves of measurement. Thus, there were 821 respondents at baseline and follow-up, and 255 respondents provided data at both waves. Four of the 24 communities at baseline dropped out of the study.

Intervention

The intervention programs consisted of 6 interactive televised training segments on evidence-based prevention programs administered approximately every 6 months; 3 of these training segments occurred during the period of our study. Television broadcasts were complemented with planning meetings, where skills learned in training were shared with other members who did not participate in the live broadcast training. Training moved from large introductory sessions to smaller audience sessions that targeted those who would actively implement prevention programs; 343 leaders participated in the first session, 196 participated in the second session, and 130 participated in the third session. The topics of the first 3 sessions were (1) identifying risk factors and protective factors of drug abuse, (2) organizing the community, and (3) understanding how to interact with local media using established community approaches for communicating public health issues and information.[40–43]

Measures

We used data from 2 surveys. The first survey—the community leader survey—included 122 items that measured leader attitudes and behaviors regarding community readiness for prevention program implementation, individual leader skills and attitudes, and coalition functioning. We used measures of coalition functioning, planning, and adopting prevention programs. The outcomes consisted of 4 scales: organizational functioning (sum of 5 items, 5-point scale from strongly disagree to strongly agree; $\alpha=0.83$; adapted from Communities United for Prevention[21]); data-based planning (15 items, 4-point scale from not at all to a lot; $\alpha=0.87$; adapted from Communities That Care[44,45] and Students Taught Awareness and Resistance[46]); benchmark achievement (12 items, 4-point scale of progress from none to completed; $\alpha=0.88$; adapted from Students Taught Awareness and Resistance[39,46]); and prevention activity progress (14 items, 5-point scale of progress from none to activity completed; $\alpha=0.90$; adapted from Communities That Care[44,45] and Students Taught Awareness and Resistance[13]). Details of scale development and measurement model analysis have been published elsewhere.[11] These 4 scores were analyzed separately and were aggregated to an overall prevention planning and adoption score as 1 outcome.

The second survey was the network survey that had both a roster of all coalition members and a question that asked each member to name how frequently they talked with each other. The survey also had 3 open-ended nomination questions that asked members to list up to 7 people to whom they go for advice about prevention issues, with whom they discuss prevention issues, and with whom they were friends. For each community, we calculated 2 network-level measures from the advice network using GAUSS software (Aptech Systems, Seattle, Wash). We first calculated density,

$$D=\frac{l}{n(n-1)}. \quad (1)$$

where l is the number of links (nominations made) and n is network size (number of coalition members). Density is determined by counting the number of reported links and dividing by the maximum number of possible links. We also calculated degree centralization,[27]

$$C_D=\frac{\sum_{i=1}\left(Degree_{Max}-Degree_i\right)}{n^2-3n+2}, \quad (2)$$

where *degree* is the number of nominations received by each person and n is network size. Degree centralization varies between zero and 1, with higher numbers indicating a more centralized network. Both measures are readily available in network analysis programs.[47]

Analysis Plan

We conducted a confirmatory factor analysis with the EQS program[48] to generate an overall prevention planning composite score—or second-order factor—on the basis of 4 separate planning scores. We then compared the analysis sample with other community leaders who were missing data at either baseline or follow-up; we used the simple unpaired t test for group comparisons on leader characteristics (role, tenure, and number of meetings attended in the last year), density and centralization, and planning and adoption outcomes. Finally, we conducted regression analyses using Stata software.[49] The following model was estimated,

$$Y_2=a+b_1Y_1+b_2Tx+b_3D_1+b_4D_2+e, \quad (3)$$

where Y_2 is 1 of the 5 outcomes in Table 1 at wave 2 and Y_1 is the same outcome at wave 1; Tx represents a treatment community; D_1 and D_2 represent network-level density at waves 1 and 2, respectively; and e is error. The community was the unit of analysis. We aggregated the data 2 ways: for only those who completed both waves 1 and 2 ($n=255$), and for all respondents who completed either wave 1 or wave 2 surveys ($n=821$).[50] We first tested intervention effects on each network score. We then included network density and centralization at waves 1 and 2 to test the mediated effects of network change on change in program planning and adoption. To increase power, we combined both STEP treatment conditions (training and technical assistance and training only), which showed no differences in network or outcome measures.

RESULTS

Table 1 shows network indicators and study outcomes for wave 1 and wave 2. The

TABLE 1—Means (SD) for Coalition Network Indicators and Outcomes for Waves 1 and 2 (n = 821): STEP, 2001–2003

	Wave 1, Mean (SD; Range)	Wave 2, Mean (SD; Range)	Unpaired t	P
Network Indicators				
Density	0.12 (0.06; 0.06–0.33)	0.15 (0.05; 0.05–0.25)	1.09	0.29[a]
Centralization	0.41 (0.14; 0.17–0.67)	0.37 (0.14; 0.16–0.61)	0.72	0.48[a]
Outcomes				
Functioning	3.67 (0.73; 1–5)	3.73 (0.70; 1–5)	1.16	0.12[b]
Planning	2.98 (0.55; 1–4)	3.04 (0.53; 1–4)	1.45	0.07[b]
Achievement	2.11 (0.43; 1–3	2.20 (0.46; 1–3)	2.87	<.001[b]
Progress	2.16 (0.52; 1–4)	2.13 (0.43; 1–4)	0.74	0.77[b]
All 4 standardized and combined	–0.038 (0.78; –2.01–1.67)	–0.037 (0.79; –1.58–1.41)	0.01	0.49[b]

Note. STEP = Steps Toward Effective Prevention.
[a]2-tailed.
[b]1-tailed.

TABLE 2—Effects of Baseline, Baseline Density, and Follow-up Density on Community-Level Attitudes and Practices Regarding Adoption of Evidence-Based Substance Abuse Prevention Programs (n = 20): STEP, 2001–2003

	Functioning	Planning	Achievement	Progress	Average Across All Outcomes
Panel[a]					
Baseline score	.62*	.58*	.71*	.66*	.75*
Wave 1 network density	.07	.35*	.00	.31	.20
Wave 2 network density	–.44*	–.44*	.04	–.47*	–.39*
R^2	0.29	0.43	0.47	0.32	0.50
Cross-sectional panel[b]					
Baseline score	.74*	.57*	.66*	.65*	.73*
Wave 1 network density	–.13	.48*	.12	.54*	.25
Wave 2 network density	–.27*	–.32*	–.08	–.38*	–.31*
R^2	0.54	0.62	0.35	0.62	0.59

Note. STEP = Steps Toward Effective Prevention. Regression model was controlled for the nonindependence of cases on their study condition.
[a]Respondents who completed both wave 1 and wave 2; n = 255.
[b]Respondents who completed either wave 1 or wave 2; n = 821.
*$P < 0.05$.

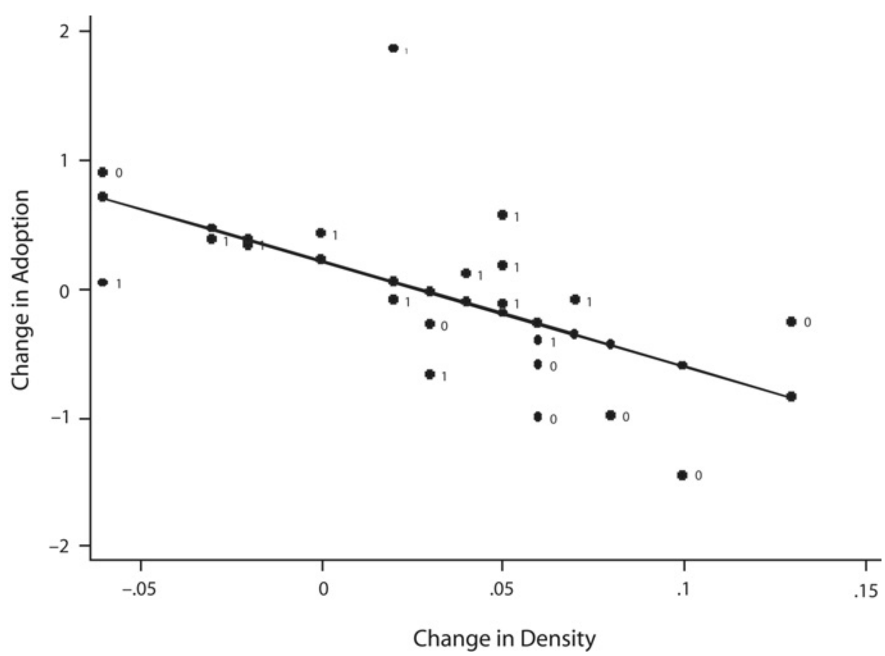
network indicators did not increase significantly between baseline and follow-up, and 2 of the 5 outcomes increased significantly overall (outcomes were not reported separately by study condition because these results have been published elsewhere). We used the 1-tailed *t* test for the outcome changes because we expected the changes to increase.

To test for main effects of the intervention, we conducted lagged regression of wave 2 outcomes on a dummy indicator for whether or not the coalition received satellite TV training. There was a significant association that indicated training improved outcomes (data not shown). Table 2 shows standardized regression coefficients for the wave 2 outcomes regressed on their baseline score, baseline density, and wave 2 density. For 3 of the outcomes and the combined score, wave 2 density was significantly and negatively associated with outcomes. Because baseline density was included in the model, the results indicate that density change was negatively associated with outcome change.[50] For example, the coefficient for organizational functioning and density at follow-up was $\beta = -0.44$, which indicated that organizational functioning was higher for coalitions that decreased their density (or lower functioning for those with increased density).

In both the panel (n = 255) and cross-sectional panel (n = 821) results, baseline outcomes were strongly correlated with follow-up outcomes. This suggests that even with a substantial portion of different individuals in the community, community-level perceptions were consistent over time. Additionally, baseline density was positively correlated with outcome change, which indicates that some basic level of interpersonal communication and connection is needed for coalitions to function and perform adequately. Table 2 shows very similar regression coefficients when data were treated cross-sectionally (including all respondents) and when data were treated as a panel (including only those present at both time points). Results for centralization were not significant (data not shown).

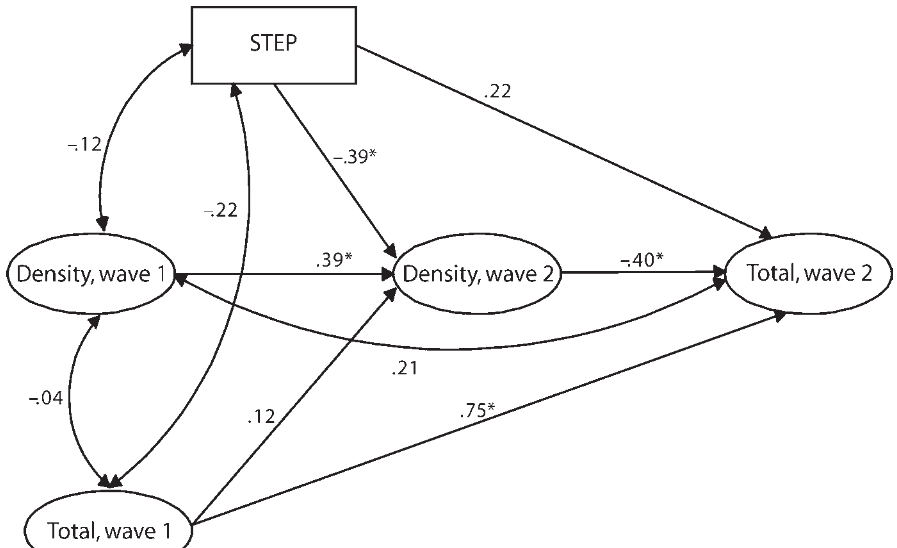
Figure 1 illustrates the change in the composite outcome by change in density. It also shows that density increased in the control communities; however, these communities had lower increases in program adoption. This indicates that perhaps the absence of an intervention in the control condition led to increased communication among members but no change in their ability to adopt programs, whereas an intervention did not change network density but did create an increase in the adoption of evidence-based practices.

To test this hypothesis, we used path analysis—estimating several regression models



Note. Coalitions are indicated by Control (0) or Intervention (1).

FIGURE 1—Change in program adoption outcomes by change in network density with Ordinary Least Squares Regression Estimate.



Note. STEP = Steps Toward Effective Prevention. The model indicates that the Steps Toward Effective Prevention intervention decreased network density. Decreased network density was associated with increased program adoption.

FIGURE 2—Path model of the effects of treatment, baseline density, and wave 2 density on community-level adoption of prevention programs.

simultaneously—to test the interaction of the intervention with changes in density and outcomes (Figure 2). We used the EQS program[48] to calculate separate path models for each outcome variable and the combined outcome. The model involved simultaneous estimation of the following 2 equations,

(4) $D_2 = {}_{-1} + {}_{-11} Tx + {}_{-12} D_1 + {}_{-13} Y_1 + e_1$ and

(5) $Y_2 = {}_{-2} + {}_{-21} Tx + {}_{-22} D_1 + {}_{-23} D_2 + {}_{-24} Y_1 + e_2$,

where Tx indicates a treatment community; D_1 and D_2 are network-level densities at wave 1 and wave 2, respectively; and Y_1 and Y_2 are the outcome variables measured at waves 1 and 2, respectively. These path models are considered to be saturated models with perfect fit to the data. Figure 2 shows that the intervention was negatively associated with density at wave 2, which indicates that being in the control condition increased density. Results also indicate that wave 1 density was positively associated with wave 2 density, and wave 1 outcomes were positively associated with wave 2 outcomes, as expected. Wave 2 density was negatively associated with wave 2 outcomes, which indicates that decreasing density was associated with lower program adoption.

DISCUSSION

Although our results are suggestive that simply increasing network communication or connectedness, or both, among coalition members will not result in improved adoption of evidenced-based practices, caution is warranted. First, the results are self-reported attitudes and practices and may not reflect actual program adoption. Second, network measures depend considerably on the question used to measure the network. In this case, we asked community leaders to indicate to whom they went for advice about prevention. Other network questions may have elicited different network structures and perhaps different results.

More communication, in the absence of promotions (satellite TV in this case) that provide information about evidence-based programs, does not lead to increased adoption of evidence-based practices. Thus, the public health system needs to continue informing coalitions and community planners about evidence-based practices.

Our results are consistent with Granovetter's strength of weak ties theory.[31] Communities that are less dense may have weak ties to other organizations that provide access to resources and power, which can be mobilized to adopt evidence-based practices. Too much density indicates that connections are directed within the group and do not provide sufficient pathways for information and behaviors to come from outside the group. Too much density leaves a coalition ineffective at mobilizing the resources it needs to adopt evidence-based prevention programs. To be sure, some density is necessary for the coalition to operate, but too much density can be counterproductive. Coalitions need to balance their efforts between creating a dense, cohesive group versus retaining some connections to outside resources.

The association between coalition density and adoption of prevention programs may be time dependent. New coalitions might need to move "from modest levels of collaboration to increasingly dense and multiplex relationships that can be used to address complex health problems." [3(p658)] Over time, however, this increasing density may become a liability, because it overly insulates the coalition from new ideas or access to new resources. On the other hand, communities that have had no coalition and that build one for the first time may require network density and centralization to get prevention planning moving. Coalition leaders must therefore be cognizant of the dynamic nature of coalition networks and networks' ability to address community concerns, but they must not sacrifice adaptation for cohesion.

Cohesion, shared mission and goals, and common values are the hallmark of community coalitions.[51] These factors may not translate into the successful adoption of prevention programs without leadership, however. That leadership can be authoritarian or egalitarian, which might be reflected in either centralized or decentralized network structures. Either one might be more successful at adopting programs but for different reasons.[52] We did not find support in this study for an association between centralization and adoption, and we hope future research will shed more light on this relationship.

The systems perspective prompted us to measure the structure of interpersonal interaction—who goes to whom for advice—rather than rely only on frequency of interactions as a measure of communication. The communication scale included in the survey did not change significantly between baseline and follow-up and was not associated with adoption, density, or changes in density. Thus, the system perspective we used uncovered significant network dynamics that were not apparent in individual reports.

The main finding from our study is that we should not assume increased communication in the form of network density will always benefit coalition functioning. In this case, it was associated with decreased ability to adopt evidence-based programs. System-level thinking and measures helped us reexamine naïve expectations about how community coalitions function and how to improve their capacity for the adoption of programs that work. ■

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Contributors

T.W. Valente originated the study and conducted the network analysis. C.P. Chou conducted the path analysis. M.A. Pentz designed and implemented the STEP trial. All authors wrote the article.

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Human Participant Protection

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